Synchronization with fractal rhythms

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Chapter 2

Strong anticipation: complexity matching in interpersonal coordination

A subtle coordination occurs within complex systems, between multiple nested subsystems. This intra-system coordination can be detected by the presence of 1/*f*-fluctuations produced by the system. But coordination can occur also between systems. Interpersonal coordination has been studied from a local point of view until now, focusing on macroscopic interactions. But the recent concept of strong anticipation introduced by Dubois (LectNotes Comput Sci 2684:110–132, 2003) suggests that interactions could occur on multiple levels between complex systems. The hypothesis is that time series in interpersonal synchronization present a matching of the complexity index (fractal exponent). Moreover it is argued that this matching is not a consequence of short-term adaptations but reveals a global coordination between participants. Eleven pairs of participants oscillated a hand-held pendulum in the in-phase pattern for 11 min, in three conditions where the coupling strength was manipulated by perceptual feedbacks. The results show a high correlation between fractal exponents irrespective of the coupling strength, and a very low percentage of local cross-correlations between time series appear at lag 0 and lag 1. These results suggest that interpersonal coordination, and more globally synchronization of participants with natural environments, is based on non-local time scales.

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Introduction

Coordination, complexity, and 1/*f-scaling*

Coordination is often considered a macroscopic feature in complex movements. From this point of view, coordination is generally referred to as inter-limb coordination, for example in locomotion (Diedrich & Warren, 1995) and in various tasks of bimanual coordination (Kelso, 1984), or as coordination between macroscopic subsystems, for example between perception and movement in reaching or avoidance behavior (Neggers & Bekkering, 2000). Coordination processes, however, are not restricted to such macroscopic (sub)systems. The activity of the brain has been described in terms of coordination between neural areas (Bressler, 2002; Bressler & Kelso, 2001), and macroscopic, behavioral coordination is supported by corresponding coordination processes in neural activities (Kelso, 1995; Lagarde et al., 2006). Coordination actually occurs at multiple levels within the system, from the macroscopic level of effectors to the microscopic level of neurons, and coordination also occurs between these different levels. As such, the organism can be considered a complex system, composed of a set of interrelated and interdependent parts that cohere into a coordinated functional system, and the macroscopic behavior can be seen as the consequence of multiple processes of coordination, which occur between multiple nested subsystems (Kello et al., 2007; van Orden et al., 2003). And because the different levels in the system act following different time scales (microscopic subsystems acting at high frequency being nested within more macroscopic subsystems acting at lower frequencies), such system is likely to present a multiple-scale dynamics.

During the last decade, a number of authors have suggested that the recurrent discovery of long-range correlation in the series of outcomes produced by complex systems could be explained by this underlying multiple-scale dynamics (Goldberger et al., 2002; Holden et al., 2009; Kello et al. 2007; van Orden et al., 2009). Long-range correlations are characterized by the presence of scaling laws, and especially in the frequency domain power $S(f)$ appears as a power function of frequency:

$$S(f) \propto {}^{1}/_{f^{\beta}} \qquad \text{(II.1)}$$

where β is the scaling exponent. A linear regression slope typically reveals this scaling law in the bi-logarithmic representation of the power spectrum, with slope $-\beta$. Long-range correlated processes are characterized by β-exponents close to 1. This scaling law, in the frequency domain, motivated the use of alternative denominations, 1/*f*-fluctuations or 1/*f*-scaling, for designating long-range correlated processes (Eke et al., 2000; Madison, 2001; Wagenmakers et al., 2004). This organization in the power spectrum is consistent with the idea of high-frequency components, or levels, nested within lower-frequency components. This scaling law has sometimes been interpreted as the additive combination of multiple, independent levels within the system. Ward (2002) suggested for example that 1/*f*-fluctuations in human behavior could arise from the combination of unconscious, subconscious, and conscious processes. Some authors have proposed that the aggregation of simple processes, acting at different time scales, could under certain conditions mimic 1/*f*-behavior in the resulting time series (Granger & Joyeux, 1980; Hausdorff & Peng, 1996). However this kind of hypothesis cannot explain why this mixture of timescales should line up in a 1/*f*-scaling relation (Kello et al., 2007).

Another, more convincing hypothesis suggests that 1/*f*-scaling origins in the complex set of interactions between components and between levels within the system (Ihlen & Vereijken, 2010; Kello et al., 2007; van Orden et al., 2003). According to Bak and Paczuski (1995), dynamical systems tend to organize themselves into critical states, characterized by meta-stability properties, and such systems are known to produce long-range correlations. The emergence of critical states is related to the presence of multiplicative interactions within the system (van Orden et al., 2003).

This so-called *interaction-dominant* perspective provides an interesting way for theorizing 1/*f*-fluctuations, because it allows to explain their ubiquity in natural systems, and also because it allows to understand the relationships that have been described between 1/*f*-fluctuations, health, adaptability and flexibility. Meta-stability expresses a subtle balance between independence and dependence. On the one hand weak interactions between components cannot support coordinated patterns of activity, and lead to erratic and unstable behavior. On the other hand strong interactions yield stereotypical behavior that cannot adapt to changing conditions. In the first case systems tend to produce uncorrelated series of performance, and the β-exponent of Eq. II.1 approaches 0. In the second case the series presents a high level of predictability, and the β-exponent grows towards 2. The subtle

balance of metastability is achieved for $\beta = 1$. $\beta = 1$ corresponds to the ideal 1/*f*, or *pink noise*, and has been discovered in a number of healthy, young and adaptive systems (Gilden, 2001; Goldberger et al., 2002; Hausdorff et al., 1995; Peng et al., 1995). In contrast, aging and disease have been shown to alter the correlational properties of performance series, either toward randomness or toward order (Goldberger et al., 2002; Hausdorff et al., 1997). In that sense, 1/*f*-scaling informs about the (organized) complexity of the system. 1/*f*-fluctuations correspond to a kind of optimal complexity, characterized by a rich network of moderate interactions within the system. The system can deviate from this optimal complexity by two opposite ways: towards disorder and randomness (in that case the system looses complexity by loosing interactions), or towards order and predictability (in that case the system looses complexity by becoming simpler). In sum, complexity can be understood as the presence of coordination processes at all levels within the system, and is revealed by the fractal properties of the series of performances produced by the system.

Interpersonal coordination and complexity

In the previous section we focused on coordination processes within a given system. But coordination can also occur between systems, for example in the case of interpersonal coordination, or when an individual has to act in coordination with the environment. Interpersonal coordination has been initially conceived at a macroscopic level. Especially Schmidt and collaborators, using laboratory interpersonal tasks, have demonstrated that when two people were asked to rhythmically coordinate their limbs, they showed behavioral phenomena identical to those found in bimanual interlimb coordination (Schmidt et al., 1990; Schmidt & Turvey, 1994). Inter-system coordination, however, can be conceived as including other levels. Notably Dubois (2003) developed the concept of *strong anticipation*, which could allow adopting a new point of view about complexity and interpersonal coordination.

Anticipation behavior has often been described, especially in synchronization experiments, for example when participants have to synchronize finger taps with the beats emitted by a metronome: in such experiments a mean negative asynchrony has been consistently reported, suggesting that participants do not react to auditory stimuli, but rather anticipate their occurrence (for a review, see Repp, 2005). Such anticipatory behavior can be underlain by the formation of an internal model that allows short-term predictions about the

time of occurrence of the next metronome signal. A number of representational models, based on phase correction (Vorberg & Wing, 1996) and/or period correction (Mates, 1994a; 1994b), have been proposed for explaining synchronization in tapping tasks (Repp, 2005). This kind of local, short-term anticipation, based on internal models and corrective processes, is referred to as *weak anticipation* (Dubois, 2003).

Strong anticipation, in contrast, is supposed to occur without reference to any internal model (Stephen & Dixon, 2011; Stepp & Turvey, 2010). From this point of view, anticipation is based on the embedding of the organism within its environment: this embedding creates a new, organism-environment system, which possesses lawful regularities that allow the emergence of anticipation.

Stephen and Dixon (2011), however, noted that two divergent approaches to strong anticipation have to be distinguished. The first one suggests that strong anticipation results from an appropriate coupling between the organism and its environment. For example, the synchronization of the rhythmic oscillations of a limb with a periodic metronome has been successfully accounted for by a model of coupled oscillators, including a parametric driving function (Jirsa et al., 2000; Torre et al., 2010). In these models, the role of the coupling term is to continuously minimize the difference between the state of the organism and the state of the external driver. Thanks to coupling, the organism does not react to stimuli, but rather anticipates their occurrence. More sophisticated models in physics have showed that during the synchronization between a follower and a leader, the presence of time delays in the leader can yield the follower to synchronize with future states of the leader (Stepp & Turvey, 2010; Voss, 2000). These models of coupled oscillators suggest that anticipation could emerge from the macroscopic properties of the organism-environment system. This conception supposes that anticipation is based on local time scales (Stepp & Turvey, 2010). In this local approach to strong anticipation, the quality of anticipation is supposed to be closely related to the strength of coupling between the two systems (Stepp & Turvey, 2010).

A second approach supposes that strong anticipation is based on a more global coordination between the organism and its environment. Stephen et al. (2008) analyzed synchronization with a chaotic metronome in a tapping task. In that case, local predictions are difficult to conceive, because of the intrinsically unpredictable nature of the external pacing signal. Results showed that tapping behavior in this situation exhibited a mix of reaction, proaction, and synchrony to metronome signals. Importantly, the authors observed a close

matching between the fractal exponents of the chaotic signals and those of the corresponding inter-tap interval series. In this global form of strong anticipation, the organism is not adapted to the states of the environment but to their statistical structure. The presence of 1/*f*-scaling in the environment seems essential in this coordination process: the organism exploits the complexity of the environment, and especially the long-range correlated structure of its evolution over time, as a resource for a more adaptive and efficient behavior (Stephen et al., 2008; Stephen & Dixon, 2011).

The concept of weak/strong anticipation has been initially designed to account for the interactions of an organism with its environment. Anticipation has in this context been investigated as a strictly uni-directional coordination: the organism anticipates the evolution of the environment, in order to optimize a given outcome. Here we extend this initial scope to the coordination between two organisms, considered as two complex systems. In that case the two systems are supposed equivalent, and their coordination lies on a mutual and reciprocal adaptation. The concept of anticipation remains relevant in this situation, but should also be conceived as reciprocal.

On the basis of the preceding discussion about anticipation, three types of interpersonal coordination could be formally distinguished. The first one is based on the principles of weak anticipation, and the involvement of internal models. From this point of view, each participant in the dyad builds a model of the behavior of its partner, in order to maintain synchronization. Recent approaches to interpersonal coordination, based on the idea of a common coding of perception and action, have emphasized this kind of representational model (Kilner et al., 2003). This form of coordination is based on local, short-term and mutual adaptations between individuals, and the quality of coordination logically depends on the amount of information that can be shared between the partners.

A second form of coordination results from interpersonal coupling, and corresponds to the local approach to strong anticipation. From this point of view, joint action is conceived as the emergent product of a system of coupled oscillators (Schmidt et al., 1990). This approach allowed to account for various empirical observations, such as the relative stabilities of distinct coordination modes, the transition between coordination modes following an increase of oscillation frequency, or the appearance of phase lags due to differences in eigenfrequencies between the two partners (Richardson et al., 2007; Schmidt et al., 1990; 2011; Schmidt & Turvey, 1994). As previously evoked, this approach supposes that joint

action patterns at the behavioral/social scale can be understood and modeled in terms of their own dynamics (Schmidt et al., 2011). Coupling involves essentially this macroscopic scale, and the strength of coupling determines the quality of coordination.

Finally, interpersonal coordination could result from a reciprocal strong anticipation process, based on a global, multi-scale coordination between the two systems. As far as we know, this last hypothesis has never been tested in interpersonal coordination. However, if 1/*f*-scaling represents an essential property for the emergence of a global form of strong anticipation, interpersonal coordination, between two systems that are likely to naturally present 1/*f*-properties, can be thought to favor such a global, multi-scale coordination process. The main prediction, in that case, should be the emergence of a close matching between the 1/*f*-scaling properties of the two systems, during the coordinated activity (Stephen et al., 2008).

Our main hypothesis, in the present paper, was that interpersonal coordination should be essentially based on global strong anticipation. We supposed that coordination processes should not be restricted to local or macroscopic levels, as suggested by weak anticipation or by the local form of strong anticipation. Both systems in the dyad being characterized by interaction-dominant dynamics, their coordination should necessarily be based the emergence of multi-scale coordination. So our main aim was to distinguish between coordination processes restricted to a local scale, and coordination processes involving multiple scales and levels within the systems.

In the present experiment we analyzed intentional interpersonal coordination in a task where two participants were instructed to synchronize oscillatory movements. The task was performed under three coupling conditions (weak, normal, and strong), according to the relative availability of information about the movements performed by the other member of the dyad.

On the basis on previous works on similar oscillation tasks (Delignières et al., 2004; Delignières et al., 2008), we expected to evidence a 1/*f*-temporal structure in the series of oscillation periods produced by each participant. We also expected to find a close matching between the correlation structures of the series produced by the two partners. However, evidencing the same 1/*f*-scaling in the series produced by the two participants of a dyad cannot per se provide evidence for a global form of strong anticipation (Stephen & Dixon,

2011). In all cases (i.e. for weak anticipation, as well as for the local and global forms of strong anticipation), a significant correlation is expected between the fractal exponents obtained from the two participants in each dyad. In the case of weak anticipation, this correlation is expected because the periods produced by one member of the dyad tend to mimic that simultaneously produced by the other. In the case of local strong anticipation, coupling is also supposed to produce a close matching of simultaneous periods. Finally, one could suppose that for weak anticipation as well as for the local form of strong anticipation, the correlation between 1/*f*-scaling should be higher in strong coupling conditions, when rich information is available about the movements produced by the partner.

In the case of global strong anticipation, the correlation between exponents is likely to occur, revealing the global, multi-scale coordination between the two partners. However, in that case correlation is not the by-product of coordination on a local scale, but represents a prerequisite for coordination. As such we hypothesize that the strength of correlation between exponents should not be dependent on the strength of coupling between individuals, from the moment where coordination occurs.

A second way for distinguishing between local and global and strong forms of coordination is to analyze synchronization, locally and on short time scales. This can be done by the computation of windowed cross-correlation functions, using a moving window of short length, between the series produced by the two partners. Clearly, one can hypothesize that both weak anticipation and the local form of strong anticipation should be revealed by significant and systematic cross-correlations, especially at lag –1, lag 0, or lag 1. A significant lag 0 cross-correlation would indicate a perfect synchrony between participants, and significant lag 1 or lag –1 cross-correlations would indicate that synchronization is based on a short-term correction process of the period produced by one participant with respect to that just previously produced by the other. In contrast, in the case of a global form of strong anticipation, synchronization is supposed to not essentially focus on the short-term, but to result from a global, multi-scale coordination between the two partners. As such, short-term dependencies are not expected to appear in a systematic manner in the windowed cross-correlation functions.

Method

Participants

Twenty-two volunteers (16 men and 6 women, mean age 24.5 years ± 2.9) were involved in the experiment, and were randomly paired into eleven dyads. Sixteen participants were right hand dominant and six left hand dominant. All participants reported having normal hearing and normal or corrected vision. They all were healthy and none had neuromuscular disorders or recent injury at the time of the study. The local ethics committee approved the experiment.

Apparatus and equipment

Participants were seated side-by-side between the two pendulums. Participant A held his/her pendulum with the right hand, and participant B with the left hand. In each dyad, participants were randomly assigned to the A or B position, and kept this position during the whole experiment. Pendulums were oscillated in the sagittal plane. The distance between the two pendulums was 1.10 m, their length was 0.48m (from the bottom of the handle to the bottom of the pendulum). A mass of 0.150 kg was fixed at the bottom of each pendulum. A potentiometer located at the rotation axis of each pendulum allowed recording the angle position (margin of error: 0.5°). The angle variations were registered at a frequency of 50 Hz, and a peak detection method (described below) was used to obtain the series of oscillation periods, which were used for further analyses. Participants saw neither the experimenter nor the screen computer.

Tasks and procedures

Participants were instructed to firmly sustain the handle with the entire hand, and to manipulate the pendulum with the wrist joint, in an abduction-adduction movement. The forearm was kept parallel to the floor, without any support. Participants were instructed to

keep silent in all conditions and between conditions, because oral communication could contribute to systems synchronization (Shockley et al., 2003).

The experiment included two separate sessions, performed on a single day. During the first session each participant performed the task in isolation, in his/her assigned position (A or B). They were instructed to oscillate their pendulum at their preferred frequency (i.e. the frequency they felt the most comfortable and they considered regularly sustainable for about 5 min). In this condition participants were asked to fix a target located in front of them, at a distance of 3.15m, and to keep their free hand on their thigh. This condition is referred to as the 'no coupling' condition in the following sections.

The second session was devoted to a set of coupled conditions, during which the participants of each dyad were instructed to perform synchronized oscillations with the two pendulums, following an in-phase pattern of coordination. They were instructed to oscillate at the preferred frequency of the dyad, as regularly as possible. This session was composed of three trials, assumed to represent three different levels of coupling between the two participants. Coupling strength was modulated through the relative availability of perceptual information between subjects, which is argued to be the basis of interpersonal coordination (Nessler & Gilliland, 2009; Schmidt & O'Brien, 1997; Shockley et al., 2003). In the 'weak coupling' condition audition was limited with earplugs and participants were instructed to visually fix a target in front of them on the wall, so that they could get information about their partner pendulum oscillations only with peripheral vision. They were also instructed to keep their free hand on their thigh. In the 'intermediate coupling' condition, visual and auditory feedbacks were fully available, and participants were invited to visually fix their partner's pendulum. They also kept in this condition their free hand on their thigh. In the 'strong coupling' condition, participants were instructed to cross their free arms (arm-in-arm), in order to add haptic information to visual and auditory feedbacks.

The order of the three conditions was randomized between dyads in order to avoid any possible learning bias. Each condition lasted 12 min, the necessary duration to collect 512 data points, which is considered the minimal to perform correct fractal analyses (Delignières et al., 2006). Because the task could be perceived as boring due to the duration of the trials, the experimenter recalled participants to keep concentrated and to maintain the required coordination, after 3, 6 and 9 min. Participants were not allowed to communicate between conditions in order to avoid a 'leader-follower' effect.

Data analysis

Oscillatory movements of pendulums were registered with the Labview software and were then analyzed with the Matlab software to obtain periods time series. A bi-directional low-pass Butterworth filter (cut-off frequency 15 Hz) was applied to the collected series of oscillatory movements (Fig II.1, top). The successive peaks of the obtained waveform series (corresponding to maximal abduction) were then detected and their times recorded as time series. Periods (in ms) were computed as the differences between two successive maximal abduction times (Fig II.1, middle). Series of relative phase (*RP*, in degrees) between the two pendulums were computed as:

$$RP = 360 \times \frac{PA - PB}{TA} \qquad \text{(II.2.)}$$

where P_A corresponds to the maximal abduction of participant A, P_B to the maximal abduction of participant B and T_A to the corresponding oscillation period of participant A. An example relative phase series is presented in Fig. II.1, bottom graph. Mean relative phase allows checking whether the requested coordination was effectively established between participants in all conditions (perfect in-phase synchronization corresponding to $RP = 0°$). Relative phase variability allows to assess the stability of coordination over a trial, and to test for the effectiveness of the experimental manipulation of coupling strength (Kelso, 1995; Schmidt & O'Brien, 1997). In the present experiment, the increase of coupling strength, from the weak coupling to the strong coupling condition, was expected to result in a significant decrease of relative phase variability.

Only the first 512 points of periods and relative phase series were preserved for further analyses. Means and standard deviations were calculated for each times series of periods and relative phase and averaged for each experimental condition.

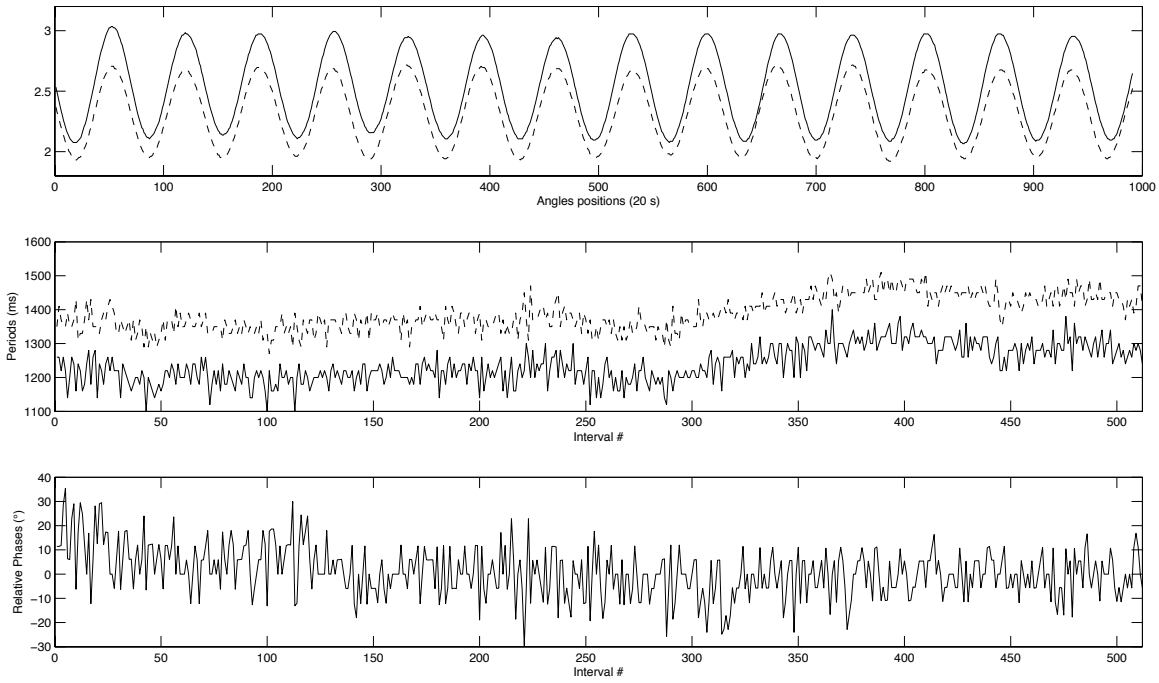

Figure II.1. Representative time series of a dyad (#4) in the 'strong coupling' condition (*solid line* corresponds to participant A, and *dashed line* to participant B). *Top*: angle positions (1000 points, 20 s). *Middle*: Individual series of oscillation periods collected over the whole trial (512 points). Data from participant B (*dashed line*) have been shifted by +150 ms for a better visualization. *Bottom*: Relative phase series over the whole trial (512 points).

Fractal exponents

We applied the detrended fluctuation analysis (DFA), in order to estimate the fractal exponent of the series of oscillation periods (Peng et al., 1993). We chose this method because it was proven to provide good estimates of fractal exponents on short series (Delignières et al., 2006). DFA is based on the analysis of the relationship between the mean magnitude of fluctuations in the series and the length of the intervals over which these fluctuations are observed. The algorithm of DFA consists of integrating the series $y(i)$ by calculating for every time point *i* the cumulative sum of the deviations of the mean:

$$Y(k) = \sum_{i=1}^{k}[y(i) - \bar{y}] \quad \text{for} \quad k = 1, 2, 3, \dots, N \tag{II.3}$$

where N corresponds to series length. This integrated series is subsequently divided in non-overlapping intervals of length n. In each interval, a least squares line is fit to the data (representing the trend in the interval). The $Y(k)$ series is then locally detrended by

subtracting to all values the linear fit value $Y_{trend}(k)$ given by a regression. For each interval length n, the characteristic magnitude of fluctuation $F(n)$ is calculated by:

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[Y(k) - Y_{trend}(k)]^2} \quad \text{(II.4)}$$

This computation is repeated for all the possible intervals lengths. $F(n)$ is linked to n by a power-law:

$$F(n) \propto n^{\alpha} \quad \text{(II.5)}$$

where α is the scaling exponent. α is estimated by the slope of the graph representing $F(n)$ as a function of n, in log-log scales. α is theoretically supposed to equal 0.5 for white noise and 1 for 1/*f*-noise.

Windowed cross-correlation analysis

This analysis consists in computing cross-correlation between the *n* first points of the series of periods produced by the two members of a dyad. The window is then lagged by one point, and cross-correlation is computed again. This process is repeated over the whole series, yielding a series of *N-n* cross-correlation coefficients. This analysis allows for revealing local dependences between the two series of periods, and their evolution over time. In order to focus on short-range dependence, we worked on windows of very short length (n = 15). Moreover, in order to avoid detecting spurious cross-correlation due to the presence of drifts in the considered windows, data were detrended within each window before the computation of cross-correlation (Delignières & Torre, 2011; Lemoine & Delignières, 2009).

Cross-correlation can be computed considering different lags between the series. We first consider lag 0, with the aim to evidence the presence of simultaneous events in the series (i.e. the presence of simultaneous long, or conversely short periods in the two series). The variables of interest were the percentages of positive, negative, and non-significant coefficients in the windowed cross-correlation series (the critical value being r_{13} = 0.5139).

In a second step, we computed windowed – cross-correlation for lag 1 and lag –1. Lag 1 and lag –1 cross-correlations are likely to reveal short-range dependence between participants: a significant positive lag 1 cross-correlation between participants A and B

suggests that B tends to mimic at time t the period produced by A at time t–1. Note that participants were arbitrarily assigned the first (A) of the second place (B) in the computation of cross-correlation. As a consequence, lag 1 and lag –1 cross-correlations are invertible and were aggregated before computing percentages.

Statistical analyses

In order to detect an effect of coupling strength on means, standard deviations, or cross-correlations, we applied one-way repeated measures ANOVAs. Scheffé post-hoc tests were conducted in order to localize significant effects. The degree of complexity matching was revealed by the Pearson's coefficient of correlation between fractal exponents of series of periods within each dyad. The results were significant for $p < 0.05$.

Results

The means and mean standard deviations of period series and relative phase series are reported in Table II.1. There was a significant effect of coupling condition on mean period ($F(3,84) = 23.49$, $p < 0.001$). Mean period was significantly lower in the three coupling conditions than in the no coupling condition ($p < 0.001$). Moreover, mean period was lower in the strong coupling than in the weak coupling condition ($p = 0.048$). There was also a significant effect of coupling condition on the mean variability of period ($F(3,84) = 4.07$, $p = 0.010$). The Scheffé post-hoc test revealed that the standard deviation of periods was lower in the intermediate coupling condition than in the other conditions ($p < 0.005$).

Mean relative phase was close to zero in all conditions, showing that participants effectively synchronized according to instructions, and there was no effect of coupling conditions on mean relative phase ($F(2,30) = 0.24$, $p = 0.79$). As expected, there was a significant effect of coupling on the mean variability of relative phase ($F(2,30) = 11.32$, $p < 0.001$): standard deviation was higher in the weak coupling condition compared to the intermediate and strong coupling conditions ($p < 0.01$), suggesting that the weak coupling was less stable than the intermediate and strong coupling conditions, which were equally stable.

Table II.1. Averaged results of time series analysis (standard deviation in italics), according to experimental conditions: mean of series (periods and relative phase), mean of standard deviation of series (periods and relative phase), mean α-DFA-exponents (periods) and coefficients of correlation between the DFA-exponents of the series of periods of the two participants of each dyad.

	No coupling	Weak coupling	Intermediate coupling	Strong coupling
Mean				
Relative phase (°)	-	-2.15	-1.67	-2.36
	-	*8.64*	*7.50*	*7.15*
Periods (ms)	1240.20	1150.00	1131.60	1099.20
	140.80	*141.60*	*137.40*	*104.80*
Standard deviation				
Relative phase (°)	-	16.67	12.76	14.04
	-	*4.56*	*4.74*	*3.17*
Periods (ms)	47.20	45.40	37.60	40.20
	20.40	*11.20*	*7.20*	*12.20*
α-DFA	1.03	1.03	0.99	1.04
	0.16	*0.15*	*0.14*	*0.20*
Correlation/α-DFA	0.47	0.97*	0.97*	0.99*

* $p < 0.001$

DFA revealed α-exponents ranging from 0.66 to 1.33. Mean values for each coupling condition are reported in Table 1. α-exponents were not significantly different between the four conditions (F (3,84) = 0.41, p = 0.748). The correlation between the DFA-exponents of the two participants of each dyad was not significant in the non-coupling condition. In contrast, this correlation was close to one in all coupling conditions (Table II.1). We present in Fig. II.2 the graphical representation of these results for the no coupling and the strong coupling conditions.

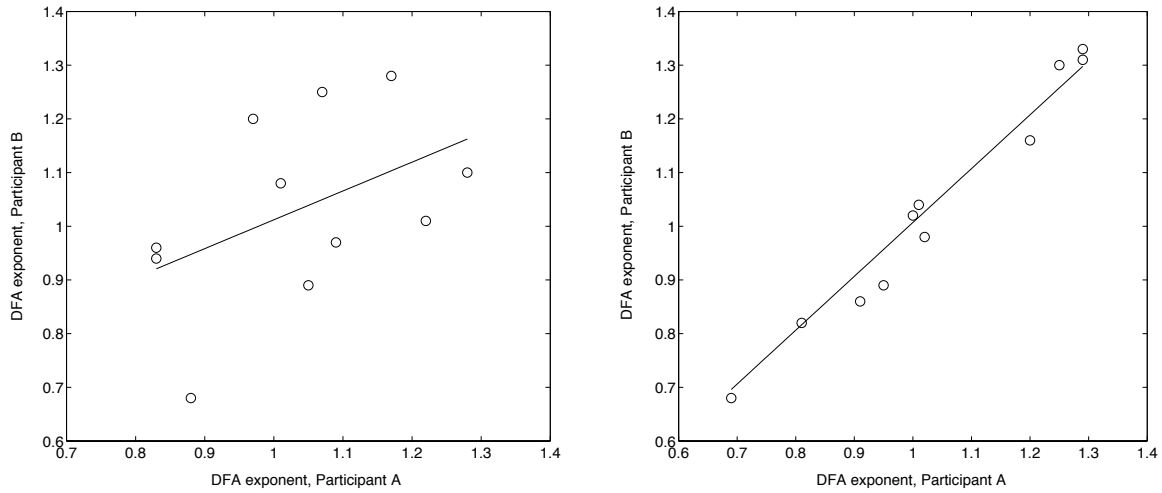

Figure II.2. Correlations between DFA-exponents (*left:* no coupling, $r = 0.47$, $p = 0.146$; *right*: strong coupling, $r = 0.99$, $p < 0.001$).

Windowed cross-correlation analyses

An example of windowed cross-correlation series is presented in Fig. II.3. This series represents the evolution over time of the local dependence between the two analyzed series. In the presented example, cross-correlation coefficients remained generally non-significant. However, some short epochs of significant dependence can be noticed, mostly positive, and more rarely negative.

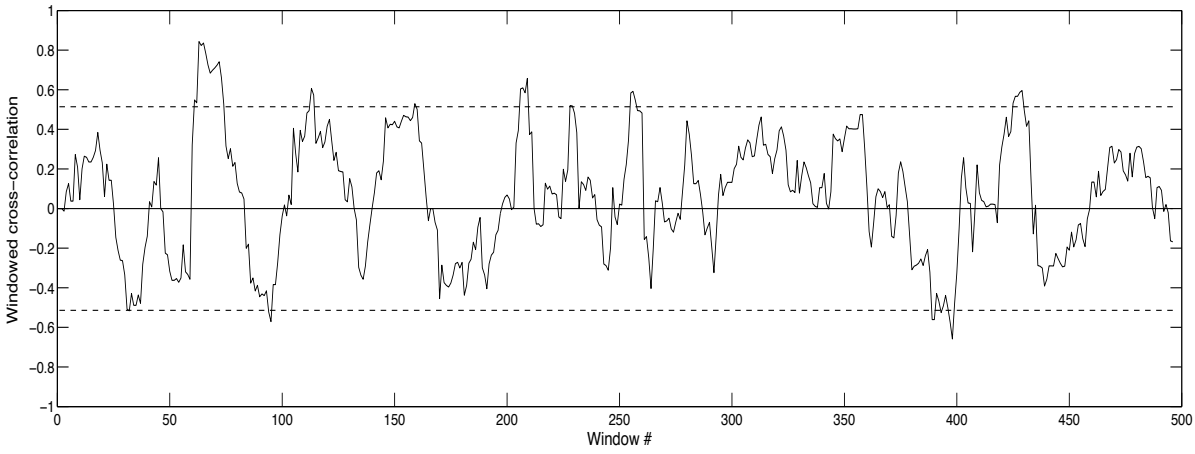

Figure II.3. Example of windowed cross-correlation series (lag +1, dyad #1, *strong coupling* condition). The *dashed lines* represent the positive and negative thresholds of significance (± 0.5139).

These results can be summarized in the form of histograms, representing the distribution of cross-correlation coefficients. We present such histograms in Fig. II.4. The two top panels represent the distribution of lag 0 cross-correlation coefficients, for all dyads, in the no coupling (left) and in the strong coupling (right) conditions. The bottom panels represent the distribution of the lag 1 and lag –1 cross-correlation coefficients. In all cases a large part of the distribution seems confined within the limits of significance. However, this graphical representation suggests an increase of positive lag 1 and lag -1 dependence with coupling.

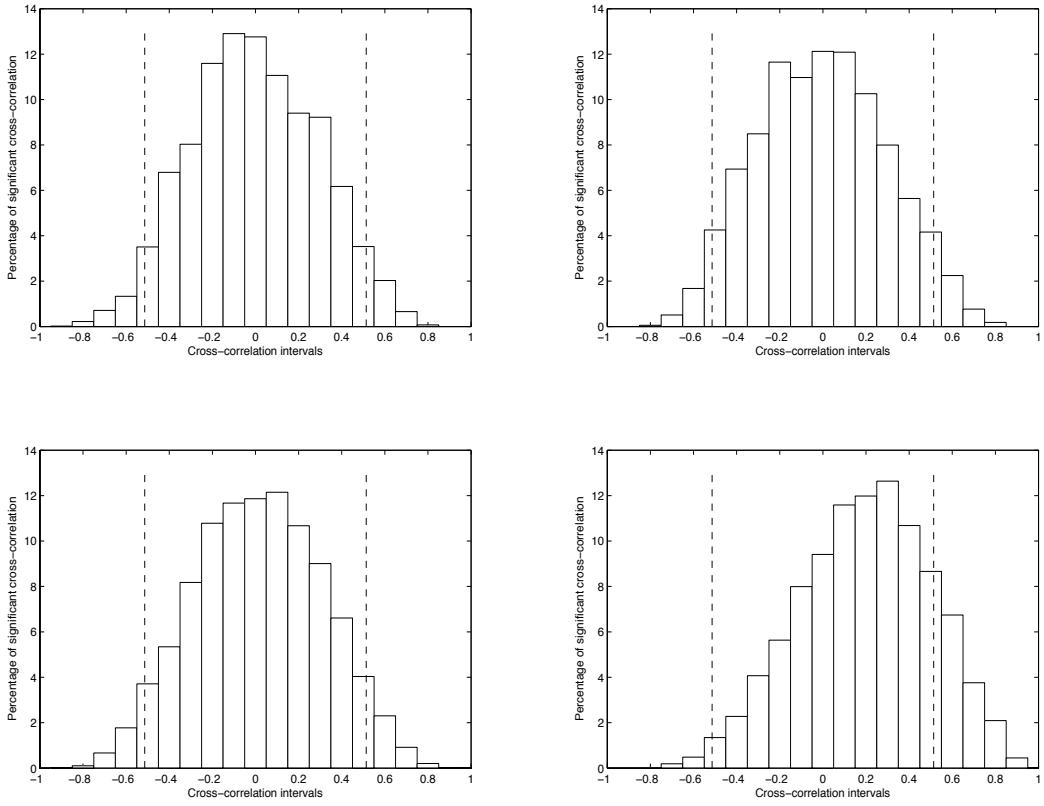

Figure II.4. Distribution of cross-correlation coefficients (*vertical dashed lines*: significance threshold) for lag 0 (*top*) and lag ± 1 (*bottom*), for *no coupling* condition (*left*) and *strong coupling* condition (*right*).

We report in Table II.2 the mean percentages of significant (positive and negative) lag 0 cross-correlation coefficients, for the four coupling conditions. There was no effect of coupling ($F(3,40) = 2.29$, $p = 0.099$), and the mean value remained moderate (9.20%), suggesting that in more than 90% of the analyzed windows, the two series appeared locally independent.

Table II.2. Mean percentages (*SD* in italics) of 15-point windows revealing significant (positive and negative) lag 0 cross-correlation, according to experimental conditions.

	No coupling	Weak coupling	Intermediate coupling	Strong coupling
Significant correlation at lag 0	7.99 *(4.70)*	10.96 *(0.94)*	8.52 *(2.47)*	9.33 *(5.85)*

Lag 1 and lag –1 analyses provided a slightly different picture. As previously explained lag 1 and lag –1 are interchangeable, and were conjointly analyzed. As can be seen in Table II.3, the percentage of windows where neither lag 1 nor lag –1 cross-correlation reached significance remained high, albeit slightly lower than the values observed for lag 0 cross-correlations. The analysis of variance revealed an effect of coupling condition ($F(3,40) = 4.15$, $p = 0.014$), and the Scheffé test showed that this percentage was lower in the intermediate coupling condition, than in the three other conditions.

The results confirm the increase of the percentage of positive correlation, as compared to lag 0 cross-correlation. There was a significant effect of coupling on the percentage of positive correlation at lag 1 or lag -1 ($F(3,40) = 6.71$, $p = 0.001$). The Scheffé test showed that this percentage was higher in the intermediate and strong coupling conditions, than in the no coupling condition. Note that the simultaneous occurrence of significant cross-correlation at lag 1 and at lag -1 remains infrequent.

Finally one could note the occasional presence of negative cross-correlation. Coupling had an effect on this presence ($F(3,40) = 8.40$, $p = 0.000$), and the post-hoc test showed that this percentage was lower in the intermediate and strong coupling conditions, than in the no coupling condition. Note that negative lag 1 and lag -1 cross-correlations never occur simultaneously.

Table II.3. Mean percentages (*SD* in italics) of 15-point windows revealing significant (positive, negative) and non-significant lag 1 and lag -1 cross-correlation, according to experimental conditions.

	No coupling	Weak coupling	Intermediate coupling	Strong coupling
Positive correlation at lag 1 and lag –1	0.24 *(0.25)*	0.16 *(0.34)*	0.84 *(1.47)*	0.37 *(0.58)*
Positive correlation at lag 1 or lag –1	8.83 *(3.09)*	16.22 *(7.72)*	28.16 *(14.57)*	22.75 *(15.97)*
No correlation	83.61 *(3.84)*	77.04 *(7.45)*	67.57 *(14.66)*	71.94 *(15.67)*
Negative correlation at lag 1 and lag –1	0.07 *(0.13)*	0.00 *(0.00)*	0.00 *(0.00)*	0.00 *(0.00)*
Negative correlation at lag 1 or lag –1	6.22 *(2.00)*	4.59 *(3.68)*	1.87 *(1.34)*	2.84 *(2.22)*

Discussion

The aim of the present experiment was to show that interpersonal coordination was based on a global form of strong anticipation, exploiting the 1/*f*-scaling properties of the two coordinated systems. The main result of this study is the very high correlation observed between the fractal exponents characterizing the series of periods produced by the two members of a dyad, from the moment where they act in coordination. This very high correlation suggests a close matching of the scaling properties of the produced series. Importantly, this correlation occurred in all coupling conditions, and was independent of the strength of coupling between participants. As previously explained, this matching of fractality and the independence between fractality matching and coupling strength clearly favors the hypothesis of a global form of strong anticipation.

The application of windowed cross-correlations allowed to control for the influence of global trends and to check whether series were still correlated on local scales. Local cross-

correlations confirm that the matching of fractal exponents cannot be entirely explained by short-term dependence between the series. The presence of significant lag 0 cross-correlation remained modest, and was not different to that observed by chance in the no coupling condition. The windowed analysis of lag 1 and lag –1 cross-correlation showed that coupling tended to induce an increase of the occurrence of positive cross-correlation, indicating that one participant of the dyad tended to adjust the period produced at time *t*, in order to mimic that produced at time *t*–1 by the other participant. However, this occurrence of short-term dependent epochs, cannot *per se* explain the close matching of fractal exponents: considering the three coupling conditions, there was no significant cross-correlation in 72.2% of the analyzed windows. As a consequence, the matching of the structures of fluctuations cannot be reduced to local interactions but is likely to reveal a more global adaptation between the two systems. In other words, the multi-scale coordination that characterizes the global form of strong anticipation does not essentially need accurate local cues for being achieved. A small amount of perceptual information appears sufficient to allow an effective matching of the statistical structures of the produced time series.

Another result that merits discussion is the presence of 1/*f*-fluctuations in the time series of oscillation periods produced by each participant. Considering the results reported in a number of recent experiments on synchronized timing, evidencing persistent correlations in synchronized oscillations is far from trivial.

Research on timing control has provided consistent evidence for the distinction between two modes of timing, namely event-based and emergent timing (Delignières et al., 2004; Delignières & Torre, 2001; Robertson et al., 1999). Event-based timing is characterized by the involvement of a central timekeeper (Wing & Kristofferson, 1973). This mode of timing is exploited in tasks requiring discrete movements, such as finger tapping. Emergent timing, in contrast, exploits the dynamical properties of the effector, considered as a self-sustained oscillator. Such oscillators present intrinsic stability properties, provided by non-temporal parameters such as muscle stiffness, that allow for a sustained production of stable frequencies of oscillation. Emergent timing is elicited by tasks involving continuous, oscillatory movements, such as circle drawing or forearm oscillations (Delignières et al., 2004; Robertson et al., 1999).

In both cases, the series of time intervals produced in self-paced conditions present persistent long-range correlations close to 1/*f*-noise (Delignières et al., 2004). However, when

participants have to synchronize with an external, regular metronome, the series of time intervals become *anti-persistent* (i.e. negatively correlated). This result has been evidenced for both modes of timing control (event-based timing: Torre & Delignieres, 2008; emergent timing: Torre et al., 2010).

Despite this similarity in results, the processes involved in synchronization are different in the two control modes. Event-based synchronization seems based on trial-to-trial corrective processes: most models suppose that the current time interval is corrected on the basis on the previous asynchronies to the metronome (Pressing & Jolley-Rogers, 1997; Torre & Delignières, 2008; Vorberg & Wing, 1996). This kind of synchronization, based on internal representations, clearly refers to weak anticipation processes. In contrast, emergent synchronization can be accounted for by a continuous coupling between the effector, considered as a self-sustained oscillator, and the metronome, modeled through a parametric driving function (Jirsa et al., 2000; Torre et al., 2011). This synchronization mode, excluding any formal representation, clearly corresponds to a local form of strong anticipation. It is important to note here that these two models are not considered as concurrent. Even if these contrasted models (event-based timing and weak anticipation one the one hand, emergent timing and local strong anticipation on the other) are paradigmatic of two historically opposite approaches of motor control (i.e. the information-processing approach, and the dynamical systems approach, respectively), they seem to account in the domain of timing control for clearly different experimental situations (Delignières & Torre, 2011).

Despite evident theoretical dissimilarities, both models present some lines of convergence: (1) in both cases, synchronization is based on an adaptation of the state of the organism to the state of the environment, (2) in both cases, adaptation remains confined to a very macroscopic, behavioral scale, (3) both models account for the alteration of the correlation structure of time interval series, which are persistent in self-paced conditions and anti-persistent in synchronized conditions, and (4) both models suppose that the quality of synchronization depends on the amount of information that is shared between the organism and the environment.

The present results and those reported by Stephen et al. (2008) showed that when participants had to synchronize with a more complex environment, the series of performances remained long-range correlated. This shows that synchronization with a regular metronome and synchronization with a less predictable signal are based on completely different processes.

The present results and those of Stephen et al. (2008) show that in that case synchronization is characterized by a close matching of the 1/*f*-scaling properties of the two systems. They also show that synchronization remains poor, when observed at the local scale. It seems clear that synchronization with a complex and unpredictable signal cannot be understood as an adaptation of the state of one system to the state of the other, but, rather, on a global adaptation of one system to the complexity of the other.

It is interesting to note that in Stephen et al. (2008) experiment participants had difficulties to match taps to signal onsets: the authors reported, for example, that the mean number of taps within a trial significantly exceeded the mean number of onsets. Synchronization was not so inconsistent in the present experiment: Even if local cross-correlations between series appear just marginally significant, participants were able to produce consistent in-phase patterns. One could suppose that this divergence in results could be due to the continuous character of the oscillatory movements imposed by the task, in contrast with the discrete nature of the tapping task used by Stephen et al. (2008). One could also consider that a human partner offers a more natural structure of variability than a formal chaotic signal, and thus allows a better synchronization. However, these two experiments show that humans are sensitive to the long-range correlation properties of their environment and exploit these properties, on the basis of global strong anticipation processes, for sustaining coordination.

Our results also support the assumption of West et al. (2008) about the concept of *complexity matching effect*. West et al. (2008) analyzed the efficiency of the transfer of information between and within complex systems. They postulated that information exchange is maximal when systems share the same complexity, and especially 1/*f*-scaling. In interpersonal coordination tasks, a very efficient information transfer must support the process of coordination between systems: in this case the best way of exchanging information is to match complexities. This interpretation implies that both systems modified their own dynamics in order to produce a stable pattern of coordination. One could argue that complex systems modify their internal functional organization (Kello et al., 2007) when they have to synchronize with another complex system.

Conclusion

Synchronization has been generally studied in laboratory experiments where participants had to adapt to quite simple, artificial and periodic signals. This kind of situation clearly elicits anticipation processes that work on local scales (i.e. weak anticipation or local form of strong anticipation), which cannot be considered a model for the processes involved in the coordination with complex, natural environments, or during interpersonal coordination. In that case, the complexity of the two systems involved in the coordination and especially their 1/*f*-structure are likely to induce a global form of strong anticipation. This raises important questions regarding the conception of artificial or virtual devices, with which humans could be invited to interact. One could suppose that the global form of strong anticipation represents a 'natural' way of anticipation, which can be engaged only if the (artificial) environment presents a sufficient level of complexity, and especially 1/*f*-scaling.

INTERMEZZO 1

Chapter 2 highlighted distributional matching between the time series produced in interpersonal coordination. The absence of local cross-correlations between time series suggested a global form of strong anticipation, implying that the observed correlation between fractal exponents was not localized at a single time scale but mainly resulted from a global coordination at multiple time scales. These results support the argument that it is possible to accurately pace movements while still producing 1/*f*-fluctuations.

As far as I know this study is the first to focus on fractal analyses in interpersonal coordination. Non-linear analysis could expose essential features in interpersonal coordination. One important challenge in the study of interpersonal coordination is to find the basis for such synchronized activities. The complexity matching effect (West et al., 2008) suggests that, when both systems (i.e. participants) share the same level of complexity (i.e. fractal fluctuations), the exchange of information is improved, resulting in accurate synchronization without any difficulties. This preliminary idea requires further analyses to be confirmed, especially in situations where participants are not instructed to synchronize but interact naturally. These perspectives are beyond the scope of this thesis, which is focused primarily on intended, absolute synchronization.

Chapter 2 led to a couple of new questions: (1) Is there any 'sensitivity' to the external rhythm participants synchronize with, or does complexity matching occur from the moment where the external rhythm presents 1/*f*-fluctuations? (2) Does complexity matching occur if the coupling is not bi-directional but becomes uni-directional, i.e. a 'follower' trailing a 'leader'?

The next sections will seek answers to these questions. In Chapter 3, participants walked in synchrony with a non-isochronous metronome. If the complexity matching is 1/*f*-dependent, a higher correlation between fractal exponents of stride time and metronome-onset time is expected if the latter presents 1/*f*-fluctuations. In Chapter 4, participants walked in a 'leader-follower' configuration with one following the other.

Chapters 3 to 5 will focus on walking tasks. Several reasons supported this choice: despite its inertia in movements (i.e. it take time to adapt) and the multi-causality of gait production (from neural sources to biomechanical constraints), walking is a relatively natural action that healthy humans perform everyday. It is a fundamental task for autonomous living: as described in Chapter 1, aging and some pathologies change the gait pattern to a less adaptable state. The use of an isochronous metronome to pace gait in Parkinson's disease has been shown to be a successful non-invasive treatment to improve gait parameters such as walking speed or stride length. But isochronous pacing also changes the stride time dynamics, from persistent fluctuations to anti-persistent fluctuations. Walking tasks thus come with two major benefits: I can seek for the properties of strong anticipation in a relatively automatic task, and I can look for new alternatives forms of pacing that preserve the $1/f$-structure of naturally produced movements.